



# Computational thinking, socioeconomic gaps, and policy implications

## SUMMARY

Numerous studies have shown that individuals from less advantaged backgrounds face poorer labor market prospects partly because they are characterized by low levels of skills, including digital skills. However, regarding digital skills, most of these studies rely on indicators of general digital competences rather than of specific information and communication technology (ICT) skills, which are particularly relevant to employability. One such skill is computational thinking (CT), which is related to problem-solving abilities in the digital domain and is often considered to be an important requirement for “high-quality” jobs. In this brief, we use IEA International Computer and Information Literacy Study (ICILS) 2018 data in order to compare the socioeconomic gap in computer and information literacy (CIL) with the corresponding one in CT. The results consistently show that students from less advantaged backgrounds have lower levels of skills than those from more advantaged backgrounds in both areas, but especially in CT.

## IMPLICATIONS

- Our findings suggest that the labor market disadvantage associated with lower levels of ICT skills among individuals from a lower socioeconomic status may be larger than previously thought. Educational policies should attempt to reduce the impact of socioeconomic background on students’ competences, addressing all the relevant dimensions of the socioeconomic digital divide and paying increasing attention to CT.
- Our results emphasize the importance of gathering evidence on various dimensions of ICT competences as opposed to only focusing on a general indicator of digital skills. Although even simple and routine jobs require individuals to be able to use ICT at some level, more and more occupations in the future will be based on advanced problem-solving abilities.

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## INTRODUCTION

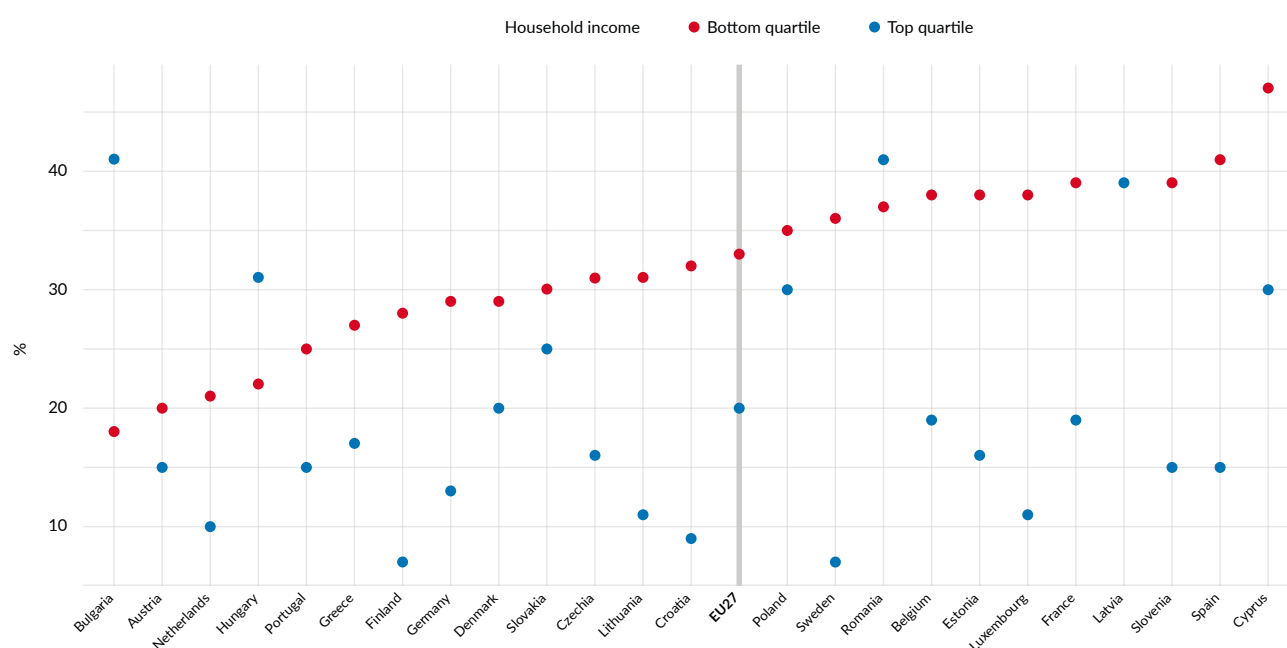
The relationship between digital skills<sup>1</sup> and labor market outcomes (e.g., type and quality of employment, wages) has been extensively studied. The emerging consensus is that higher levels of information and communication technology (ICT) skills tend to correlate positively with more favorable labor market positions (see e.g., Machin and Van Reenen 1998; Fairlie 2006; DiMaggio and Bonikowski 2008; Acemoglu and Autor 2011; Atasoy et al. 2013; OECD 2013; Peng 2017). That is, digital literacy can help workers be more productive, earn higher wages, find a job after a period of unemployment, or start their own business.<sup>2</sup> Perhaps most importantly, while “basic” digital skills are found to enhance employability, advanced ICT skills lead to higher wages (e.g., Atasoy et al. 2013).

This evidence raises concerns about the extent and the consequences of the digital divide, especially if patterns of

ICT inequality begin at an early age. First, students from more advantaged backgrounds tend to have a greater exposure to digital technologies and tools, both at school and at home, compared to those from less advantaged backgrounds. Second, this makes individuals from lower socioeconomic status backgrounds more likely to end up with lower levels of digital competences. Third, given that digital skills are a fundamental asset in the modern knowledge-based economy—some degree of ICT proficiency is required even in low-skilled or semi-skilled occupations—these individuals face a higher risk of being excluded from the best jobs, possibly trapped in rapidly disappearing “routine jobs” (provided they can get one).

Recent evidence from the Digital Economy and Society Index (DESI) (European Commission 2020) (see Figure 1) confirms that in most European countries low socioeconomic status is associated with low levels of digital skills.<sup>3</sup>

Figure 1: Percentage of individuals with low digital skills by income quartile



Source: The underlying data are taken from Eurostat's ICT survey of households and individuals (Eurostat 2020).

**Note:** For Latvia the percentage of individuals with low digital skills in the top income quartile (blue dot) coincides with the value in the bottom quartile (red dot).

1. In this brief, the terms “skills” and “competences” are used interchangeably.
2. It should be noted that indicators of digital skills employed in the cited research are quite diverse, ranging from access to a personal computer at home to patterns of internet use or specific measures of computer problem-solving ability. Also, note that the studies are largely observational in nature and, as such, do not necessarily specify a causal link from having a given level of digital skill to a position on the labor market.
3. The low level of skills reported in Figure 1 refers to a composite measure of digital skills derived from indicators of proficiency in four major domains: (a) information, (b) communication, (c) creative content, and (d) problem solving. The underlying data come from Eurostat's survey, ICT usage in households and by individuals (Eurostat 2020). For each of the major domains, participants in the survey are asked questions about computer and internet activities performed within the three months prior to the survey; for each domain, four to seven activities are selected. The objective is to distinguish between computer and internet users who have “basic” skills and those who don't, rather than precisely measure individuals' proficiency in these areas. A person is classified as having low level of digital skills if they report to have performed none of the indicated activities in up to three of the four major domains; if the person hasn't performed any activities in all domains, they are classified as having no digital skills. Further details concerning how the indicator of digital skills is computed can be found in the methodology section of the Digital Economy and Society Index (DESI). Note also that the four domains listed above, along with safety, are core competences in the JRC Digital Framework for Citizens (DIGCOMP) (Carretero et al. 2017).

When addressing the importance of digital skills in the labor market, the conventional approach is to look at digital competences as an encompassing concept. However, a growing literature on routinization and job polarization shows that it is increasingly relevant to separate abstract/cognitive skills from routine (and manual) skills. Labor market returns are very high for abstract and cognitive skills, whereas routine skills are less and less in demand (Autor and Dorn 2013; Goos et al. 2014; Spitz-Oener 2006). This consideration underscores the importance of distinguishing between general digital competences on the one hand, and computational thinking (CT) on the other. The former refers to one's ability to use computers to search for, acquire, and process information, to create content, and to communicate with others<sup>4</sup> (Fraillon et al. 2020, Chap. 2). CT instead refers to one's ability to identify, test, and implement possible algorithmic solutions to the problem at hand and to analogous problems that might arise in a new context or situation<sup>5</sup> (Fraillon et al. 2020, Chap. 3). CT is consistently regarded as one of the most important competences that individuals need to possess in order to be able to cope with future changes in the labor market (Czaja and Urbaniec 2019; Rakowska and Cichorzewska 2016; Slavinskis et al. 2015).

## DATA AND MAIN RESULTS

The aim of this brief is to look at how the socioeconomic gap in general digital competences differs from the corresponding one in CT. For this purpose, data from the International Association for the Evaluation of Educational Achievement (IEA) recently released 2018 wave of the International Computer and Information Literacy Study (ICILS)<sup>6</sup> are used. ICILS 2018 tests grade 8 students from various countries in two areas, (a) computer and information literacy (CIL) and (b) CT<sup>7</sup>, using a task-based approach. That is, besides a set of self-assessment questions asking students about how often they use ICT and for what purposes, ICILS measures

the digital literacy of its participants with a set of tasks requiring the students to use their actual skills. They are then assigned numeric scores reflecting their proficiency levels.

Following relevant studies, high socioeconomic status is measured employing two different proxies: (a) whether at least one of the parents has a tertiary degree, and (b) whether at least one of the parents is employed in a professional or specialist occupation (i.e., one-digit ISCO-08 1, 2, and 3 occupations<sup>8</sup>).

Figure 2 shows socioeconomic gaps in CIL and CT test scores for several countries. In this figure, the dots correspond to a difference in average test scores between a high-status group (i.e., students whose parents have a tertiary degree or students whose parents work in a professional or specialist occupation) and a low-status group (i.e., students whose parents have below tertiary education or students whose parents do not work in professional or specialist occupations). The higher the dots, the larger is the magnitude of the socioeconomic gap in test scores. Red dots correspond to gaps on the CIL test, whereas blue dots refer to gaps in the CT test. One should also note that CT was an optional component of ICILS 2018, which was taken up by 9 of the 14 ICILS 2018 countries.

In general, the size of both gaps varies significantly across countries and across both proxies for family background. For instance, the CIL test score gap based on parental education is equal to 30 points in Finland and nearly 60 points in the Republic of Korea (hereafter Korea, for ease of reading) or Luxembourg.<sup>9</sup> Similarly, the corresponding CT test score gap is less than 40 points in Denmark and Finland, but it exceeds 60 points in Luxembourg and in the United States. Furthermore, with respect to parental occupation, the gaps in CIL test scores range from 20 points in Korea to more than 50 points in Luxembourg. In a similar vein, the gaps in CT test scores vary from a little over 20 points in Korea to more than 60 points in Luxembourg.

4. With reference to the DIGCOMP framework, it is close to the competence areas 1, 2, and 3.

5. This is close to the DIGCOMP competence area 5.

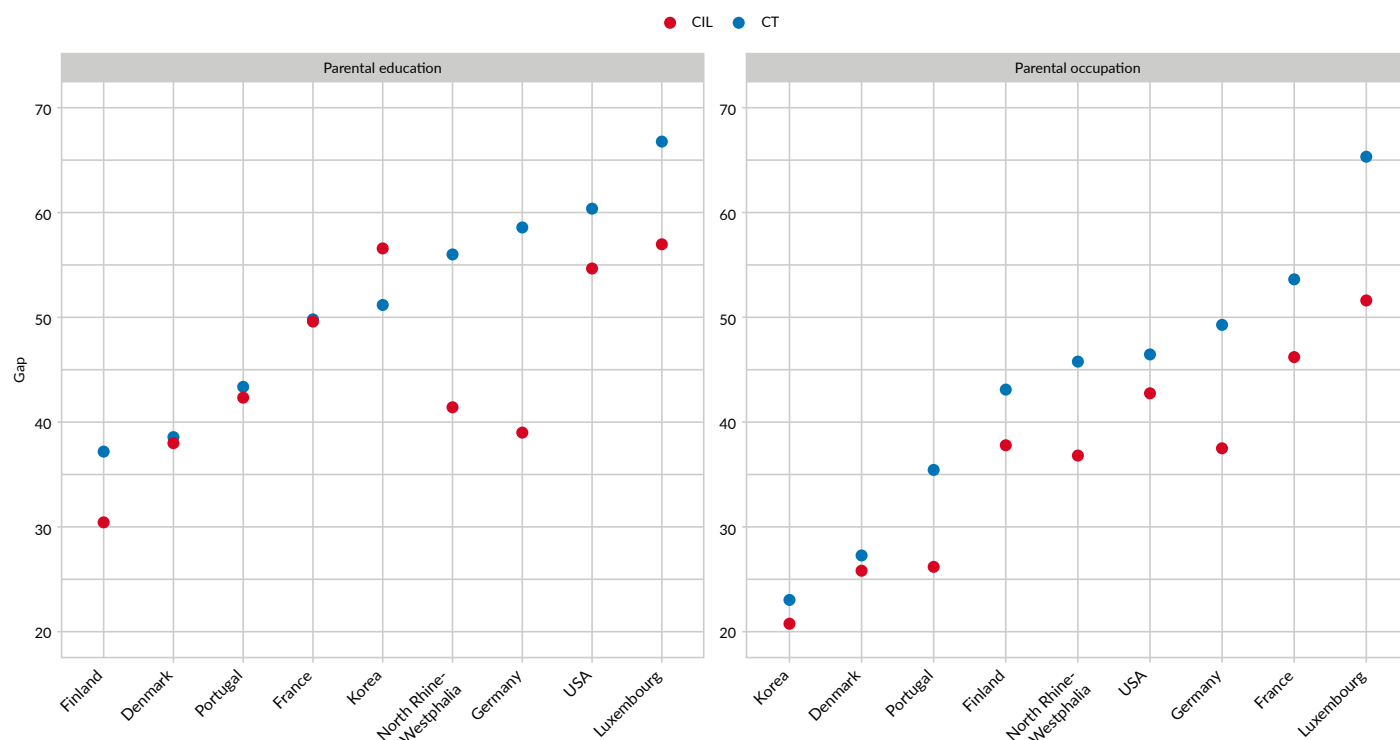
6. ICILS is an international comparative survey targeted at grade 8 students (or grade 9 in some countries) and aiming to measure their ICT skills.

7. This is the first time that students participating in ICILS were tested in CT.

8. ISCO = International Standard Classification of Occupations; see <https://www.ilo.org/public/english/bureau/stat/isco/>

9. Both CIL and CT tests were scaled to have a mean of 500 points and a standard deviation of 100 points. Thus, a gap of 50 points on a given test corresponds to a difference of half the standard deviation. Note, however, that individual scores on these tests cannot be directly compared, as the scores were scaled with respect to different populations. That is, a student's score on the CT test reflects that student's position relative to the mean of the nine countries (equally weighted) which participated in the test in 2018. Similarly, a student's score on the CIL test reflects her position relative to the mean of all the countries (equally weighted) which participated in the CIL test. Because the underlying populations are different, individual test scores cannot be compared directly across the tests.

Figure 2: Socioeconomic gaps in CIL and CT test scores



Two main findings emerge clearly from Figure 2. First, regardless of what proxy for socioeconomic status is employed, and in line with expectations, students from more advantaged backgrounds perform better in both CIL and CT tests, compared with their peers from less advantaged backgrounds (i.e., the gaps in test scores, as represented by the dots in Figure 2, are statistically significantly greater than 0 in all the countries).

Second, again irrespective of the proxy used for socioeconomic status, the gap in CT test scores tends to be larger than the one in CIL test score (exceptions are Korea and, to a lesser extent, France), although this pattern is more pronounced when looking at parental occupation.

Having identified that there are consistent differences in socioeconomic gaps between CT and CIL test scores, the next step is to test whether such differences are overall statistically significant. To that end, we pool all the data from

the countries which participated in both the CIL and CT tests and regress CIL and CT test scores on our measures of socioeconomic status (separately for parental education and parental occupation), including country fixed effects in the specification of our model. Our interest lies in the estimated coefficient for the indicator of socioeconomic status. This corresponds to the difference in test scores between the high-status and low-status groups, net of country-specific time-invariant characteristics. The results indicate that, overall, the difference is greater for the CT test than for the CIL test. More precisely, the estimated gap in CT scores between the high-education and low-education groups is 45 points in the case of the CIL test and 52 points in the case of the CT test. These differences are statistically significant at conventional levels. Similarly, the estimated gap in scores between the high occupational status and the low occupational status groups is 40 points on the CIL test and 45 points on the CT test. Again, these differences, while not large in absolute terms, reach statistical significance.





## CONCLUSION

Our analysis, which relies on ICILS 2018 data, shows that there are already significantly different levels of ICT skills among 15-year-old students depending on their family background. Moreover, when looking separately at CT and CIL test scores, the socioeconomic gap in CT test scores is consistently larger than the corresponding one in CIL test scores. This has two main implications.

First, our results emphasize the importance of gathering evidence on various dimensions of ICT competences as opposed to only focusing on a general indicator of digital skills. Although even simple and routine jobs require individuals to be able to use ICT at some level, more and more occupations in the future will be based on advanced problem-solving abilities. These competences are expected to be associated with better jobs, higher productivity, and overall better labor market outcomes. As mentioned earlier, higher levels of computer proficiency are associated with higher employment probabilities (relative to individuals with basic ICT skills) (e.g., Atasoy et al. 2013; OECD 2013), and higher wages (also relative to individuals with basic ICT skills) (DiMaggio and Bonikowski 2008; Atasoy et al. 2013). Second, if the advanced digital problem-solving abilities (i.e., CT) were not considered, one would underestimate the extent to which individuals from disadvantaged socioeconomic backgrounds are likely to be penalized in the labor market because of their poor endowment of ICT skills.

Our results suggest that students from lower socioeconomic status are likely to experience unequal opportunities in the future labor market, as they are less endowed with “premium” skills expected to be in high demand. This may potentially lead to larger social inequality, income and job polarization, lower social mobility, and higher poverty rates.

In light of the evidence presented here, we argue that policies should address all the relevant dimensions of the socioeconomic digital divide. While it is important to ensure that all students are endowed with the basic ICT “tools” (e.g., PC/notebook/tablet, internet connection) as well as with the general information retrieval/communication/interaction abilities, this is not sufficient. The labor market will demand an increasing number of workers with cognitive abilities that allow them to develop imaginative solutions to complex problems, often by using digital technologies (including artificial intelligence). Such cognitive abilities, which are typically represented with the term “computational thinking,” involve a set of “hard core” competences that include logic, mathematics, reading capacity, and critical thinking, besides creativity. The schools of the future—and of the present—need to be able to deliver high quality education on all these dimensions and for all students, irrespective of their socioeconomic background.

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The International Association for the Evaluation of Educational Achievement, known as IEA, is an independent, international consortium of national research institutions and governmental agencies, with headquarters in Amsterdam. Its primary purpose is to conduct large-scale comparative studies of educational achievement with the aim of gaining more in-depth understanding of the effects of policies and practices within and across systems of education.

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ISSN: 2589-70396

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Please cite this publication as:

Karpiński, Z., Biagi, F., & G. Di Pietro (2021, January). *Computational thinking, socioeconomic gaps, and policy implications*. IEA Compass: Briefs in Education No. 12. Amsterdam, The Netherlands: IEA.